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Driving forces of CO_2 emissions and mitigation strategies of China's National low carbon pilot industrial parks

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HIGHLIGHTS

- China's national low-carbon industrial parks pilot program is analyzed.
- The STIRPAT model is used to reveal how driving factors affect CO_2 emissions.
- A regional analysis confirms distinct low carbon development patterns are needed.

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ABSTRACT

In an effort to address climate change, in 2013 China launched the world's largest government-driven carbon emission reduction programme, the National Low Carbon Industrial Parks Pilot Programme (LCIPPP). This paper analyses this newly developed pilot program. To deepen our understanding of the causes and the impact of industrial park CO_2 emissions, we use the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model and data from 20 pilot industrial parks involved in the LCIPPP for the period 2012–2016. This study quantitatively evaluates the effect of CO_2 emissions on output, energy structure, energy intensity, industrial structure, R&D intensity, and population change in different regions and nationally through an elasticity coefficient method. The results confirm that an increase in output and energy intensity is a dominant contributor to the growth of CO_2 emissions whereas an increase of the share of tertiary industry and R &D intensity has significant effects on reducing CO_2 emissions. The elasticity of energy intensity and renewable energy consumption on CO_2 emissions in the eastern region of China is the highest, indicating that using renewable energy to reduce CO_2 emissions for the industrial parks is more effective in the eastern region as compared to the central and western regions of the country. The elasticity of population is significantly negative in both the central and western areas while it is positive in eastern part of China, thereby illustrating that promoting labour intensive industries will be an effective way to reduce CO_2 emissions for the industrial parks in China's central and western regions. Our study reveals that differentiated low carbon development pathways should be adopted. Concrete policy implications for reducing CO_2 emissions are also provided.

1. Introduction

China, the largest CO_2 emitter in the world, has made an impressive effort in recent years to move towards a low-carbon future. China has committed to reduce its carbon intensity by 60–65% from 2005 levels by 2030, increasing non-fossil-fuel energy to 20% of its energy mix by 2030 and peaking its carbon emissions by 2030 [1].

While industry is one of the key driving forces of economic growth in China, it is also responsible for approximately more than 60% of the nation's total energy consumption and CO_2 emissions. China's industrial emissions far outweigh any other sources of greenhouse gases (GHG) in the country. Therefore, managing energy consumption and CO_2 emissions in industrial sectors is essential to achieve the transformation to a low-carbon economy. Progress in this area will contribute measurably to global efforts to mitigate climate change and ensure sustainable development.

Industrial parks have been one of the most effective approaches which China has taken in its recent and significant industrial

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development. According to the *Directory of China's Development Zone 2006* published by the National Development and Reform Council (NDRC), China had 222 state-level industrial parks and 1364 provincial-level industrial parks in 2006 [2]. Up to 2017, there are more than 600 state-level industrial parks [3], including 219 National Economics and Development Zones [4] and 156 Hi-tech Industrial Development Parks. [5] Development of industrial parks has been one of the main contributors of economic growth for local areas. Most industrial parks cluster industries such as automotive, mining, petroleum, coal, and steel. These all require very large capital investments and rely heavily on intensive resources, energy and labour inputs. Industrial parks face the challenge of increased environmental pollution, in particular increased CO_2 emissions. Therefore, it is essential to improve the overall eco-efficiency of industrial parks and manage their GHG emissions in a systematic and rigorous manner.

To accelerate China's transformation to a low-carbon economy and increase its industrial competitiveness, the Ministry of Industry and Information Technology (MIIT) and the NDRC jointly launched the Low Carbon Industrial Park Pilot Programme (LCIPPP). This pilot programme is one of the major policies in the industry sector that supports the achievement of industrial energy-savings and green development. It has been implemented for four years from 2014 to 2017 and covers 51 parks selected from a total of 106 parks. The LCIPPP is not the first pilot programme for industrial parks initiated by the Chinese central government. Other major initiatives include: the Eco-Industrial Park Demonstration Programme (EIPDP), led by the Ministry of Environmental Protection (MEP); the Circular Transformation of Industrial Parks (CTIP), led by the NDRC and the Ministry of Finance (MoF). The CTIP aims to generate much higher productivity and efficiency of resource utilization. The EIPDP aims to develop industries capable of maintaining ecosystem balance and the sustainable use of natural resources. The primary objective that significantly differentiates the LCIPPP from the other related programmes is that LCIPPP has been dedicated to reducing the intensity and overall CO_2 emissions in industrial parks through upgrading the industrial structure, promoting technology innovation and enhancing carbon management ability. The pilot parks use carbon accounting as a tool to quantify and measure carbon emissions, to set targets for carbon emissions, to make decisions and to design road maps for mitigation strategies which include the elimination of outdated high-energy-consuming industries, the transformation of existing industries to low-carbon production and the development of more low-carbon industries. To date no studies have summarized the latest progress of China's LCIPPP and measured the effectiveness of the programme. Our study reviews the LCIPPP in China, and comprehensively examines CO_2 emissions at the industrial park level based on data from 20 pilot industrial parks. This paper also analyses the corresponding mitigation strategies that these industrial parks might adopt by taking their geographical distribution into consideration. More specifically, compared with the existing research which primarily focuses on the low carbonization of one particular industrial park, this study includes many more industrial parks where different leading industrial sectors are clustered. The findings seek to contribute to the policy making process to achieve low carbonization for industrial parks. China's progress and experience in implementing the LCIPPP will not only help industrial parks in China, but also encourage other countries to strive towards achieving the low carbon economy.

2. Literature review

Industrial parks are essential for industrial cluster development which promotes efficient resource utilization and reduces infrastructural costs by achieving economies of agglomeration. [6] Abundant studies are focused on GHG emission mitigation through industrial symbiosis activities in Eco-Industrial Park (EIP). For instance, Hashimoto et al. [7] present Kawasaki Eco-town as a case study to demonstrate potential performances of CO_2 emission reduction though industrial symbiosis. Harris' [8] research also shows that firms operating as a community within an EIP and engaging in industrial symbiosis collaborations could realize greater benefits collectively. These include GHG emission reductions through by-product exchanges and thermal recovery, which is better than if each business optimized its performance in isolation. Geng et al. [9] find that the Shenyang Economic and Technological Development Zone applied an industrial symbiosis strategy to reduce total energy consumption and energy-related emissions. Liu et al. [10] cite the Tianjin Economic Development Area (TEDA) in China and claims that it reduced its CO_2 emissions by 42 thousand tons (as of 2012) through industrial symbiosis activities, and they also demonstrate how to implement comprehensive development of industrial symbiosis for the purpose of GHG emission mitigation in China from a theoretical perspective. Pan et al. [11] build a four-level modeling framework for EIP research which emphasizes the aspects to be considered in future industrial ecology including carbon emission, reuse of by-products, water consumption and energy consumption. Although many EIPs were not initially built for carbon reduction purposes, industrial symbiosis could help reduce carbon emissions. Similar opinions are also adopted by other researchers, such as Liu et al. [12], Zhang et al. [13], Dong et al. [14] and Kastner et al. [15]

Considering the existing research, low-carbonization of industrial parks continues to be examined through various perspectives. Some scholars focus exclusively on how low carbon technologies help to reduce CO_2 emission. Hassiba et al. [16] make use of the recently proposed CO_2 integration approach to explore carbon management options across an entire industrial park. In order to explore the lowest cost footprint reduction options for a given industrial park, Midthun et al. [17] first present an approach to the systematic design of low cost carbon integration networks for industrial parks through an integrated analysis of sources, utilization and storage options, as well as capture, separation, compression and transmission options. Hassiba and Linke [18] propose an optimization-based approach to explore synergies across heat integration and carbon capture, utilization and storage (CCUS), and renewable energy in industrial parks. Another popular approach is to discuss the carbon accounting and carbon footprint of industrial parks. Fang et al. [19] establish an embodied carbon accounting framework based on emergy to identify the input–output structure and embodied carbon emission flows of the industrial park. Dong et al. [20] introduce a tiered hybrid life-cycle method to trace the carbon footprint of industrial parks. Some studies examine energy flows and energy conservation in industrial parks. Hackl and Harvey [21] investigate options for clusters of chemical processing plants to decrease their energy and emission footprints, such as increasing heat integration, replacing fossil feedstocks with renewables and bio-refinery integration [22]. Other studies choose some industrial parks as case studies for low carbon development. The research of Huang et al. [23] on low carbon practice applied targets to Caohejing High-Tech Industrial Park of Shanghai as a case study. Wang et al. [24] and Liu et al. [12] use Suzhou Industrial parks as a case study to assess GHG emissions and to identify potential mitigation measures.

In China, the output value of over 1700 national and provincial industrial park account for more than 60% of the nation's gross industrial output value [25]. Although industrial parks greatly contribute to national economic development, they are accompanied by environmental drawbacks, including more carbon emissions and environmental pressures [24]. While EIPs in China have been the subject of academic research, discussion and publication, the focal point of existing literature has been the EIPs, not the low-carbon industrial parks. Most research papers about EIPs regard the reduction in carbon emissions as a by-product of industrial symbiosis. There are few articles that specifically study low-carbon industrial parks. Most research focuses on a single aspect of low carbon development, or a single park, and fail to conduct a mixed and comprehensive analysis, especially in combination with nation-wide policies that constrain CO_2 emissions. Existing

literature also lacks quantitative analysis of the driving factors of CO_2 emissions at the industrial park level. This is due, in part, to the fact that industrial parks seldom undertake carbon accounting. As a new initiative, China's national LCIPPP is the first and the largest scale industrial low-carbon initiative promoted by the government in the world. This paper seeks to address the lacuna in research about China's LCIPPP performance. It summarizes the best practices of the LCIPPP, and uses econometric methods to assess the performance of 20 pilot industrial parks while seeking to identify the driving factor affecting CO_2 emissions. This study reveals some traits and trends of the industrial park low-carbonization pathway. The research may provide insight not only for other industrial parks in China and those in developing countries, while at the same time contributing valuable observations for the world with respect to low-carbonization economic activities and strategies for mitigating climate change.

3. The development process of LCIPPP in China

3.1. The context for LCIPPP

In 2013, the LCIPPP was implemented by China's central government, the MIIT and the NDRC. The two ministries jointly issued a *Notice of the Launching of Pilot Projects for National Low-Carbon Industrial Parks* as a guideline for the programme [26]. Any industrial park listed in the *Directory of China's Development Zone 2006* could apply for a LCIPPP certificate. Initially provincial branches of the MIIT and the NDRC chose 2 or 3 candidates from each province. Upon submission, the candidate list was then verified and approved by the MIIT and the NDRC. The ministries nominated the final list for inclusion in the LCIPPP giving consideration to geographic disparity and industry distribution. In the first batch, a total of 55 out of 106 industrial parks were approved, with 51 of them entering the pilot implementation stage. From the end of 2017 to the beginning of 2018, these industrial parks will go through evaluation and certification. According to the *13th Five-Year GHG Emissions Control Work Plan* [27] issued by China's State Council, in the future, the LCIPPP will be expanded to include 80 industrial parks, making it a major step in Chinese industry's efforts to tackle climate change.

3.2. The current status of the LCIPPP

The LCIPPP has been implemented for more than 4 years. From a geographical perspective, China's unbalanced economic growth and regional disparity was reflected in the pilot industrial parks' geographical distribution, 40% pilot industrial parks in eastern, 33% in central and 27% in western (Fig. 1). Many of the parks specialize in one or more leading industrial sectors. Industrial parks that feature classic heavy manufacturing, such as iron and steel, construction materials, nonferrous metals and petrochemicals account for 32% of the total. Environmentally friendly industry and hi-tech industrial parks account for 15%, and the rest are mixed industries parks.

In 2012, the Gross Domestic Product (GDP) of the 51 pilot industrial parks totalled 2.25 trillion RMB, accounting for 4.16% of the national GDP. The value-added industrial outputs of these pilot parks totalled over 1.37 trillion RMB, accounting for 6.7% of the country's total industrial value added. Some of the pilot industrial parks made crucial contributions to local economic success. For instance, from 2012 to 2016, the GDP of TEDA soared from 220.5 billion RMB to 304.9 billion RMB, maintaining an average annual growth rate of 10.5% and accounting for 11.4% of the GDP in Tianjin. Suzhou Industrial Park contributed an average 14% of Suzhou city's GDP during the trial period. The GDP of Suzhou Industrial Park increased from 173.8 billion RMB to 215 billion RMB from 2012 to 2016 [29]. However, due to intensive energy consumption, industrial parks are also a major contributor to GHG emissions. According to incomplete statistic surveys, the CO_2 emissions in 2012 from energy (electricity and fossil fuel) consumption and waste incineration of the 51 industrial parks totalled 318.36 million tonnes. With national carbon emission over 8.62 billion tonnes for China that year [28], these 51 industrial parks accounted 3.69% of the national total. Since the launch of the LCIPPP, nearly 60% of the pilot parks have seen a reduction in their carbon emissions per unit of industrial value added. Some industrial parks experienced increases in total energy consumption and emissions levels but a decrease in carbon emissions intensity [29].

4. Data and methodology

In order to measure the impact of different driving factors on the CO_2 emissions of the industrial parks, and provide guidance for the future design of low-carbon models, this study selected 20 participating pilot parks. These industrial parks were then subject to quantitative analysis to evaluate their performance during the pilot's initial time period.

4.1. Sample selection

A sample of 20 participating industrial parks were selected giving due regard to the regional diversity, considering the representativeness of the sample and the data availability. Regional inequality is a multidimensional phenomenon in China. In the *Seventh Five-Year plan,* which was approved in 1983, the State Development Planning Commission divided the country into three economic regions: eastern, central and western. The three regions differ drastically in terms of economic development. The unbalanced economic growth and regional disparity also were reflected in the pilot industrial parks development, so we choose 8 out of the 20 sample parks locate in the eastern area, 6 in the central region, and 6 in the western part of the country. The sample industrial parks not only vary in regions but also in leading industries. We summarize the leading industries of the sample parks in Table 1.

Through exploratory data analysis, we observe that the total carbon emissions continued to increase but did so at a significantly slower pace after the pilot programme was initiated in 2014. The increase rate of CO_2 emissions from 2015 to 2016 was only 0.66%, which was significantly lower than the 6.84% from 2012 to 2013. The CO_2 emissions per unit of GDP shows a mild yet decreasing trend (Fig. 2).

The overall share of the tertiary sectors rose steadily to nearly 30% in 2016 from 2012. While increasing, renewable energy has yet to become a significant source of energy usage. As of 2016, renewable energy accounted for less than 4% of the total energy consumed. The research and development (R&D) intensity (R&D expenditure as a share of GDP) rose slightly from 4% in 2012 to 4.4% in 2016 (Fig. 3).

We further group the sample industrial parks into eastern, central and western regions and analyze each group (Fig. 4). The eastern industrial parks generally have a significantly larger share of tertiary sectors and a higher growth rate. Industrial parks in the eastern regions also have lower energy intensity. In 2012, the base year for the LCIPPP, the average energy intensity of the western industrial parks was 4 times that of the eastern industrial parks. In 2016, this difference was still significant, but the energy intensity dropped faster in the western region than in the eastern and central regions, with a 20% decrease from 2012 to 2016. Despite the overall low share of renewable energy consumption to the total energy consumption, the eastern industrial parks exhibit a significant advantage in both the total amount and growth rate of renewable energy consumption. The amount of renewable energy consumed by western industrial parks was the least among the three regions in 2012. However, western industrial parks saw their renewable energy usage growing steadily, and equaled the central industrial parks in 2016.

In the eastern regions, industrial parks' R&D intensity was significantly higher than the other two regions, but it had a slower growth rate. R&D intensity in western industrial parks was the lowest, but it

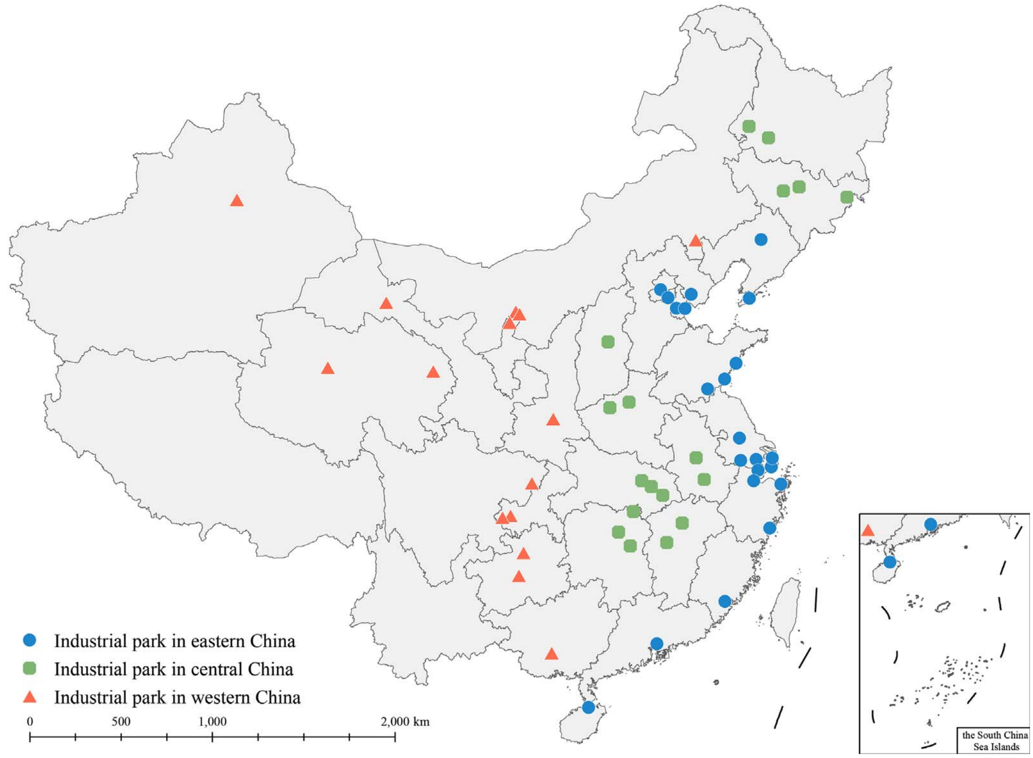

Fig. 1. The geographical distribution of the national low carbon pilot industrial park sites. (Note: Central including both central and northeast).

had a relatively high growth rate. Contrary to the slow growth rate in the east and the fast growth rate in the west, the R&D investment of central regions exhibits a fluctuating pattern. The R&D intensity in the central group decreased in 2013, while rising slightly in 2014 and falling again in 2015. It was not until 2016 that the figure returned to its 2014 level.

Based on the 2012 statistics, the central regions, rather than the eastern, had the highest share of high-tech industry output as a

Table 1
List of the sample industrial parks.

Region	Industrial park	Leading industries
East	Tianjin Binhai Hi-Tech Industrial Development Zone	Information Industry, Modern Services
	Shenyang Economic and Technological Development Zone	Equipment Manufacturing, Automobiles & Parts, Pharmaceutical Chemicals
	Shanghai JinQiao Economic & Technological Development Zone	Automobiles, Information & Communication Industry, Household Electrical Appliances, Biomedicine, Food Industry
	Yixing Environmental Technology Industrial Park	Energy-saving and Environment-friendly Industries
	Suzhou Industrial Park	Electronic Information
	Xiuzhou National High-tech Zone	Textile Industry, Equipment Manufacturing, New energy and New Materials
	The National Linyi Economic and Technological Development Area	Construction Machinery, Chemicals, New Energy
	Rizhao Economic-Technological Development Area	Automobiles & Parts, Paper manufacturing, Grain and Oil Processing
Centre	Jilin Chemical Industry Circular Economy Pilot Park	Petrochemical Industry
	Changchun Economic & Technological Development Zone	Automobiles & Parts, Biochemical Industry
	National Hefei Economic and Technological Development Area	Household Electrical Appliances, Equipment Manufacturing, Automobile Industry
	Anhui Chizhou Economic Development Zone	Nonferrous Metals, Building Materials, Electronic Information, High-End Equipment Manufacturing
	Nanchang National High-tech Industrial Development Zone	Biomedicine, Photovoltaics, Aviation, New Materials, Electronic Information
	Luoyang National New and High Tech Industry Development Zone	Biomedicine, New Materials, Energy Conservation and Environmental Protection, Intelligent Equipment Manufacturing
West	Zunyi Economic and Technological Development Zone	Equipment Manufacturing, Light Industry with Local Characteristics, Electronic Information
	Inner Mongolia Etog Economic Development Zone	Coal Industry, Electricity, Chemicals, Building Materials
	Inner Mongolia Chifeng Hongshan Economic Development Zone	Nonferrous Metals, Pharmaceutical Industry, Equipment Manufacturing, Textile Industry, Energy & Power
	Chongqing Bishan National High-technology Zone	Electronic Information, Food and pharmaceutical industry, Equipment Manufacturing (Automobile and motorcycle industry included), Shoemaking
	Sichuan Dazhou Industrial Park	Energy & Chemical, Metallurgical and Building Material, Automobile Machinery, Producer Services
	Ningxia Shizuishan High-tech Industrial Development Zone	New Materials, Automobiles & Parts, Machinery Manufacturing

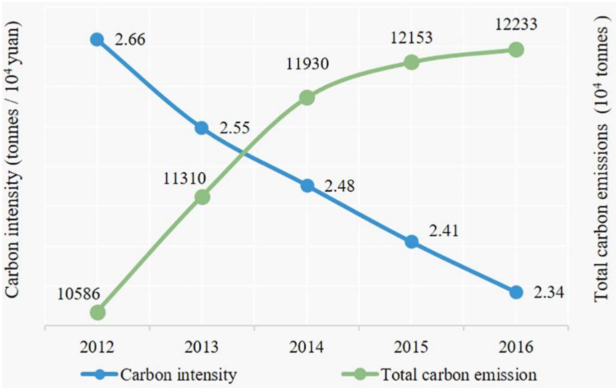

Fig. 2. Carbon intensity and total carbon emissions of the 20 sample industrial parks.

percentage of total industrial value added. However, since 2014, this figure for the central industrial parks steadily decreased from 45% in 2012 to 37.5% in 2016. By contrast, for the western group, the share of high-tech industry outputs dramatically rose, from a mere 16.2% in 2012 to 31% in 2016.

The analysis confirms that localisation and institutions-related aspects cannot be overlooked. Spatial factors need to be taken into consideration in order to understand better potential development pathways of industrial parks.

4.2. Model specification

We use the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model to analyze how different factors contribute to changes in CO_2 emissions in the industrial parks over the pilot period. The STIRPAT model has been widely applied in studies on the driving factors of energy consumption and GHG emissions trends. Martínez-Zarzoso and Maruotti [30], Lin et al. [31] and Zhang et al. [32] use the STIRPAT model to investigate country-wide patterns of carbon emissions. The STIRPAT model is also adopted by researchers to study carbon emissions in specific countries, such as Malaysia [33], Pakistan [34] and China [35,36]. Some researchers utilize the STIRPAT model to analyze carbon emissions for the regions in China, such as in Xinjiang province [37], Guangdong province [38], also cities in China, such as Beijing [39] and Chongqing [40]. However, this is the first time the STIRPAT model has been used to conduct a comparative analysis at the industrial park level.

Ehrlich and Holdren [41] first introduced the IPAT model, where *I* represents the human impact on the environment, typically measured as the emissions level of a pollutant; *P* denotes population size; *A* represents a society's affluence and *T* represents technology:

$$I = P \times A \times T \tag{1}$$

Because the *IPAT* model is simple and has limitations, Dietz and Rosa [42] propose the STIRPAT model as follows:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{2}$$

Taking logarithms on both sides of the equation leads to the following:

$$\ln I_{it} = a + b(\ln P_{it}) + c(\ln A_{it}) + d(\ln T_{it}) + e_{it} \tag{3}$$

where *a* represents a constant term; *P*, *A* and T are the same as those in Eq. (1); *b*, *c* and *d* represent the elasticity of environmental impacts with respect to *P*, *A* and T, respectively; e_{it} is the error term; and subscript *i* denotes the units, which is industrial parks here, *t* denotes the year.

In this study, we refine the STIRPAT model to conduct the empirical analyses. First, we define the carbon elasticity, which refers to the proportional change in carbon emissions due to a change in driving forces. Then, we calculate the component elasticity for each driving force using panel data. The explained variable *I* is the total CO_2 emissions, which is the carbon emissions from the fossil fuel, industrial production processes, net inflows of electricity or heat power and other sources in the industrial park, as measured in ten thousand tons. The explanatory variable *P* is measured by the employed population, *A* is measured by the industrial value added, and *T* is measured by the R&D intensity. As noted in York et al. [43], additional factors can be added to the basic STIRPAT model as long as they are conceptually appropriate for the multiplicative specification of the model. To conduct a comprehensive analysis of the factors that influence CO_2 emissions, we add the energy intensity, energy structure, and the industry structure into Eq. (3). Eq. (3) could be rewritten as follows:

$$\ln CO_{2it} = a + b(\ln PEM_{it}) + c(\ln IVD_{it}) + d(\ln RD_{it}) + \delta EI_{it} + \theta ES_{it} + \lambda IS_{it} + e_{it} \tag{4}$$

where *EI* represents energy intensity and *ES* represents renewable energy as a share of primary energy consumption. *IS* represents industrial structure, measured by the percentage of tertiary sector output to the total output. *PEM* represents the employed population. The employed population in 2012 is the actual number of employed. Due to missing data, the number of employed in year 2013–2016 is estimated by the

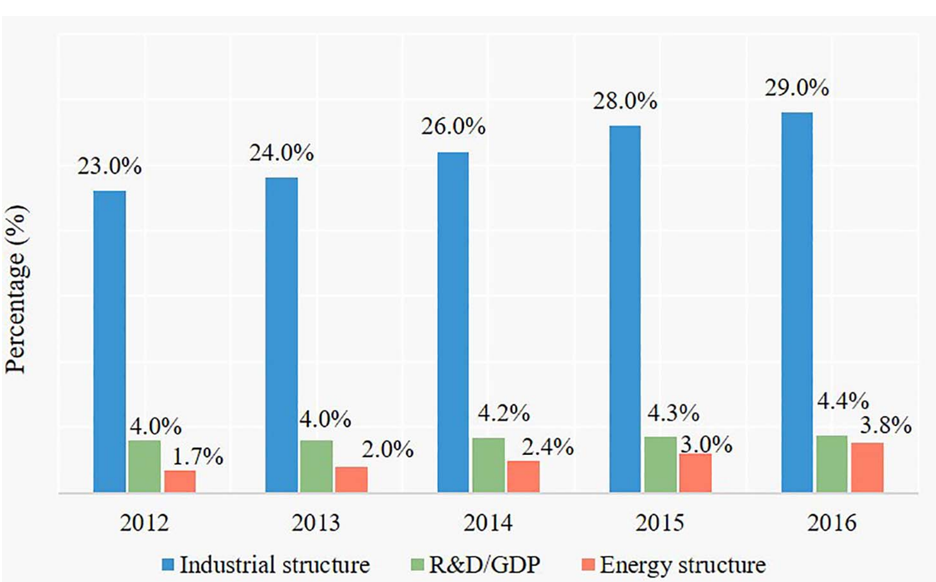

Fig. 3. Industrial structure, R&D intensity and energy structure of the sample industrial parks. (Specifically, industrial structure is the percentage of tertiary sector output to the total output; R&D intensity is the percentage of R&D expenditure to GDP, and energy structure is the percentage of renewable energy to total primary energy consumption).

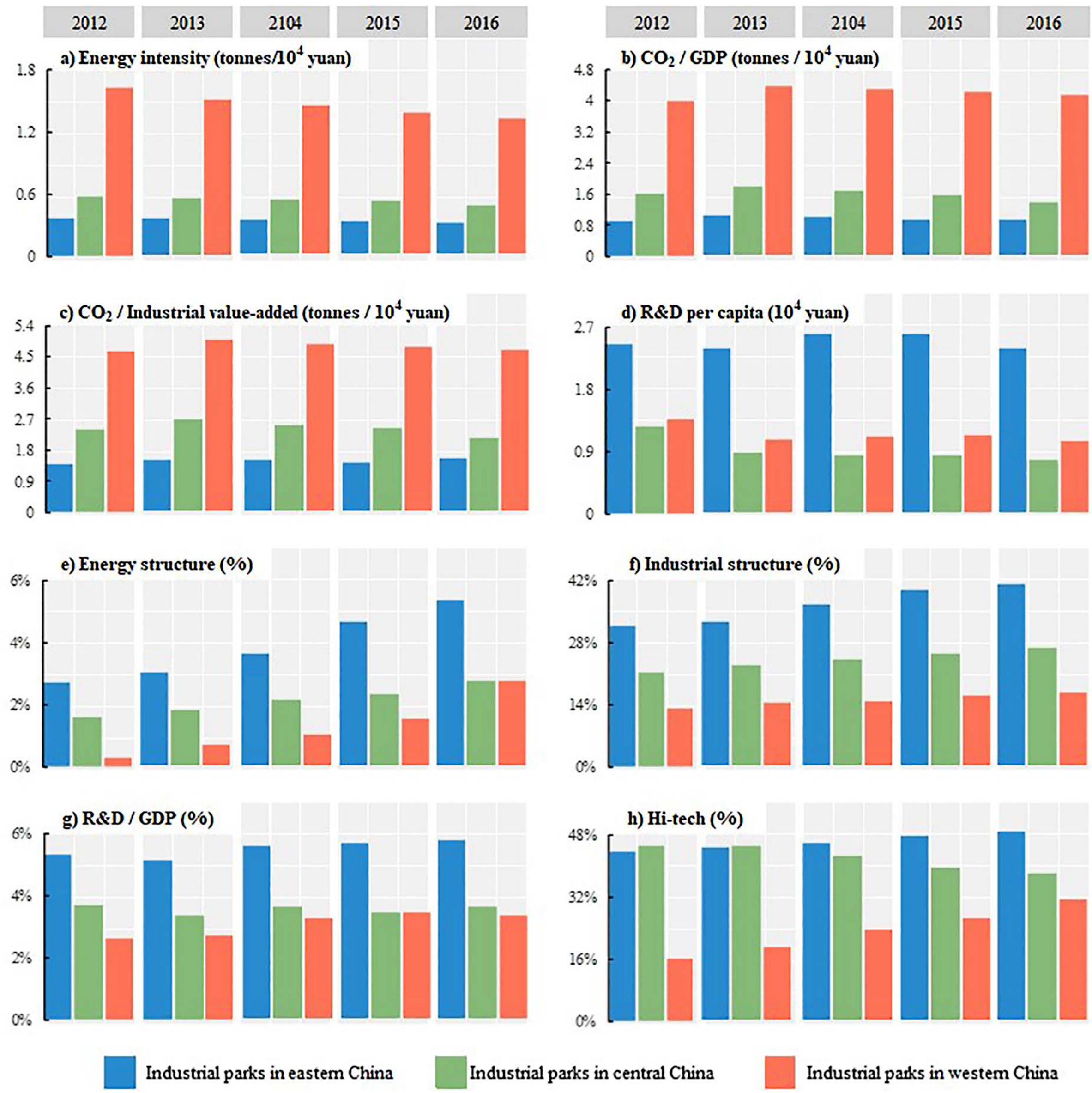

Fig. 4. The variables of the sample industrial parks in the different regions in China.

base year data in 2012 and the annual change in the corresponding provincial employment rate. *IVD* represents the industrial value-added. *RD* represents the R&D intensity. Regional effects can be captured via regional-specific dummy variables. We add regional dummy variables in Eq. (4) and rewrite it into:

$$\ln CO_{2it} = a + b(\ln PEM_{it}) + c(\ln IVD_{it}) + d(\ln RD_{it}) + \delta EI_{it} + \theta ES_{it} + \lambda IS_{it} + Dummy \times [\varepsilon(\ln PEM_{it}) + \eta(\ln IVD_{it}) + \sigma(\ln RD_{it}) + \phi EI_{it} + \xi ES_{it} + \varphi IS_{it}] + e_{it} \quad (5)$$

In this case, a series of dummy coded (0/1) variables are used, where the dummy takes 1 for any industrial park located in eastern provinces and 0 otherwise; the same principle was applied for the central and western regions. The descriptive statistics of the variables used in the regression is listed in Table 2.

Table 2
Descriptive statistics of the variables.

Variables	Definition	Mean	STD. DEV.	Min	Max
CO_2	Total CO_2 emissions	593.049	726.323	10.131	3380.08
PEM	Employed population	11.898	18.269	1.7	110.446
IVD	Industrial value-added	304.724	285.987	30.77	1136.49
RD	R&D intensity	0.042	0.248	0.002	0.101
ES	Energy structure	0.026	0.030	0.000	0.147
EI	Energy intensity	0.718	0.889	0.068	3.993
IS	Industrial structure	0.259	0.149	0.013	0.548

5. Empirical results and discussion

We use ordinary least squares (OLS) regression to analyze the different driving forces on the total CO_2 emissions of the selected 20 samples. Regional analysis is also conducted to measure the regional effects by using dummy variables. The time period ($t = 5$) was much smaller than the cross-sectional samples $N = 20$, which generates little possibility of pseudo-regression[1]. The unit root test and cointegration test were not necessary in our study.

[1] Only long-term series panel data require a unit root test and cointegration test to rule out pseudo-regression.

Table 3
Linear OLS regression with time and area as fixed effects.

Variables	(3-1) $\ln(CO_2)$	(3-2) $\ln(CO_2)$	(3-3) $\ln(CO_2)$	(3-4) $\ln(CO_2)$
ln(*PEM*)	0.401^{***}	0.401^{***}	0.289^{***}	0.271^{***}
	(0.077)	(0.078)	(0.082)	(0.079)
ln(*IVD*)	0.701^{***}	0.698^{***}	0.658^{***}	0.642^{***}
	(0.083)	(0.085)	(0.083)	(0.083)
ln(*RD*)	−0.094	−0.097	-0.239^{**}	-0.278^{**}
	(0.092)	(0.094)	(0.117)	(0.113)
ES	4.021	3.849	1.003	−0.242
	(3.634)	(3.787)	(3.667)	(3.789)
EI	0.985^{***}	0.985^{***}	1.074^{***}	1.084^{***}
	(0.072)	(0.073)	(0.081)	(0.081)
IS	-2.019^{***}	-2.030^{***}	-2.221^{***}	-2.301^{***}
	(0.666)	(0.681)	(0.648)	(0.658)
Time Effect		YES		YES
Area Effect			YES	YES
Constant	0.509	0.483	0.796^{*}	0.745
	(0.408)	(0.444)	(0.451)	(0.482)
Observations	100	100	100	100
R-squared	0.722	0.722	0.738	0.742

Standard errors in parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

5.1. Overall analysis

Table 3 presents the estimated results of the linear effects of output, energy structure, energy intensity and the other factors on CO_2 emissions at an aggregate level. ln(*PEM*) exhibits significantly positive impacts on carbon emissions, which indicates that a larger industrial park tends to have a higher emission level. *IS* has an elasticity of −2.019 (result (3-1)), indicating that a 1% increase in the industrial structure will lead to a 2.019% decrease in total CO_2 emissions when other variables remain constant. Similar results are also found when the regression is used with fixed effects of time and area (result (3-2), (3-3), (3-4)). The elasticity of ln(*IVD*) and *EI* is 0.701 and 0.985 (result (3-1)), respectively. This indicates that a 1% increase in output and energy intensity will lead to 0.701% and 0.985% increases in total CO_2 emissions respectively, when the other dependent variables remain constant. The coefficients of *ES* are not statistically significant in all regressions while the coefficients of ln(*RD*) are negative and statistically significant at a confidence level of 5% when the area effect is controlled (result (3-3)) or both the area and time effects are controlled (result (3-4)).

5.2. Regional analysis

We add the regional dummy variable *Deast* to the model and create 6 interaction items *Deast*∗*ES*, *Deast*∗*EI*, *Deast*∗*IS*, *Deast*∗ln(*RD*), *Deast*∗ln(*IVD*) and *Deast*∗ln(*PEM*). The OLS regression results are reported in Table 4.

The signs and significance of the coefficients of ln(*PEM*), ln(*IVD*), *EI*

Table 4
OLS regression at the regional level: eastern region.

Variables	(4–1) $\ln(CO_2)$	(4–2) $\ln(CO_2)$	(4–3) $\ln(CO_2)$	(4–4) $\ln(CO_2)$	(4–5) $\ln(CO_2)$	(4–6) $\ln(CO_2)$
ln(*PEM*)	0.385^{***}	0.283^{***}	0.322^{***}	0.301^{***}	0.328^{***}	0.515^{***}
	(0.077)	(0.073)	(0.098)	(0.101)	(0.107)	(0.147)
ln(*IVD*)	0.719^{***}	0.792^{***}	0.817^{***}	0.893^{***}	0.791^{***}	0.698^{***}
	(0.086)	(0.080)	(0.075)	(0.118)	(0.118)	(0.121)
ln(*RD*)	−0.025	−0.025	0.030	0.033	−0.015	0.011
	(0.101)	(0.090)	(0.098)	(0.097)	(0.093)	(0.101)
ES	8.339^{***}	12.34^{***}	10.64^{***}	10.33^{***}	10.04^{***}	8.556^{**}
	(2.714)	(3.027)	(3.736)	(3.723)	(3.768)	(3.788)
EI	0.970^{***}	0.987^{***}	0.994^{***}	0.982^{***}	0.991^{***}	1.033^{***}
	(0.069)	(0.066)	(0.069)	(0.071)	(0.070)	(0.072)
IS	-2.091^{***}	-2.045^{***}	-1.472^{*}	-1.515^{*}	-1.504^{*}	-1.514^{*}
	(0.663)	(0.639)	(0.829)	(0.820)	(0.849)	(0.784)
Deast∗*ES*	−5.565	-19.65^{***}	-17.18^{***}	-17.57^{***}	-17.30^{***}	-16.89^{***}
	(3.969)	(4.494)	(5.691)	(5.624)	(5.631)	(5.458)
Deast∗*EI*		2.250^{***}	2.531^{***}	4.465^{**}	5.391^{**}	5.182^{**}
		(0.409)	(0.549)	(1.776)	(2.102)	(2.214)
Deast∗*IS*			−1.000	0.415	0.063	0.157
			(1.186)	(1.600)	(1.538)	(1.509)
Deast∗ln(*RD*)				0.389	0.845	0.807
				(0.337)	(0.596)	(0.619)
Deast∗ln(*IVD*)					0.224	0.316
					(0.198)	(0.206)
Deast∗ln(*PEM*)						−0.278
						(0.191)
Constant	0.681	0.283	0.225	−0.089	0.201	0.451
	(0.427)	(0.385)	(0.414)	(0.546)	(0.544)	(0.601)
Observations	100	100	100	100	100	100
R-squared	0.725	0.765	0.769	0.772	0.776	0.780

Standard errors in parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

Table 5
OLS regression at the regional level: central region.

Variables	(5–1) $\ln(CO_2)$	(5–2) $\ln(CO_2)$	(5–3) $\ln(CO_2)$	(5–4) $\ln(CO_2)$	(5–5) $\ln(CO_2)$	(5–6) $\ln(CO_2)$
ln(*PEM*)	0.331***	0.321***	0.317***	0.327***	0.354***	0.359***
	(0.078)	(0.083)	(0.080)	(0.086)	(0.090)	(0.091)
ln(*IVD*)	0.729***	0.782***	0.886***	0.881***	0.890***	0.878***
	(0.087)	(0.091)	(0.101)	(0.103)	(0.105)	(0.107)
ln(*RD*)	0.011	0.002	0.051	0.053	0.018	0.018
	(0.099)	(0.094)	(0.092)	(0.092)	(0.099)	(0.099)
ES	1.745	3.672	1.070	1.275	1.911	1.963
	(3.905)	(4.316)	(4.201)	(4.304)	(4.439)	(4.471)
EI	0.975***	0.936***	0.803***	0.812***	0.809***	0.811***
	(0.066)	(0.057)	(0.050)	(0.056)	(0.058)	(0.058)
IS	−1.994***	−2.345***	−3.177***	−3.169***	−3.353***	−3.342***
	(0.657)	(0.661)	(0.551)	(0.552)	(0.573)	(0.578)
*Dcentral***ES*	10.18***	−0.068	11.47*	10.99*	13.08**	23.39**
	(3.444)	(4.987)	(6.168)	(6.393)	(5.938)	(9.982)
*Dcentral***EI*		0.795***	1.578***	1.549***	0.939***	1.543**
		(0.203)	(0.271)	(0.276)	(0.285)	(0.589)
*Dcentral**ln(*PEM*)			−0.450***	−0.564***	−0.654***	−0.931***
			(0.098)	(0.119)	(0.121)	(0.307)
*Dcentral**ln(*RD*)				−0.079	0.063	0.537
				(0.068)	(0.087)	(0.394)
*Dcentral***IS*					4.145***	2.259
					(1.461)	(2.187)
*Dcentral**ln(*IVD*)						0.415
						(0.355)
Constant	0.845*	0.562	0.662*	0.654*	0.473	0.520
	(0.438)	(0.458)	(0.348)	(0.344)	(0.381)	(0.370)
Observations	100	100	100	100	100	100
R-squared	0.732	0.752	0.780	0.781	0.788	0.790

Standard errors in parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

remain the same compared with the regression results at an aggregate level as shown in Table 3. The coefficients of ln(*RD*) are not significant when the interaction items are included in the model. The elasticities of *IS* remain negative, but the confidence level changes. *ES* shows positive coefficients in all regression results at a confidence level of 1%, but it is worth noting that the elasticities of interaction item *Deast*∗*ES* exhibits statistically significant negative signs, making the coefficients of *ES* for the eastern industrial parks −7.31, −6.54, −7.24, −7.24, −7.26 and −8.334, respectively (result (4-2)–result (4-6)), at a confidence level of 1%. The interaction item *Deast*∗*EI* indicates a positive and statistically significant coefficient, which means that compared with the western and central industrial parks (when *Deast* = 0), the energy intensity in the eastern part of China has larger elasticity.

Compared with the aggregate regression results in Table 3, the coefficients of variables ln(*PEM*), ln(*IVD*), *ES*, *EI* and *IS* exhibit the same sign and significance with the interaction items of dummy variable *Dcentral* when all the driving forces are included in the model (Table 5). The coefficients of ln(*RD*) are not statistically significant. However, *Dcentral*∗*ES* shows positive elasticity with a confidence level at 1% in result (5-1), 10% in result (5-3) and result (5-4), and 5% in results (5-5) and (5-6), which is opposite from what we get in the regression for eastern region. Thus, for the central industrial parks, as the share of clean energy increases, the total CO_2 emissions also increase when other factors remain constant. The coefficients of *Dcentral*∗*EI* are positive and statistically significant, indicating higher *EI* elasticities in the central area. *Dcentral*∗ln(*PEM*) has negative elasticities, and the coefficients are significant at a confidence level of 1%; the elasticities of LPEM in the central area are -0.133, -0.237, -0.3, and -0.572, which indicates that an increase in population size would lead to a decrease in the total CO_2 emissions for the central region.

When the interaction items of the regional dummy variables *Dwest* with the six driving factors of total CO_2 emissions are included in the model, the coefficients of ln(*PEM*), ln(*IVD*) and *EI* exhibit the same sign as those in the aggregate model (Tables 3 and 6). The elasticities of ln(*RD*) are negative but not significant, except in result (6-5). *IS* has negative coefficients with a 1% confidence level in result (6-1) and 5% in result (6-2). The interaction *Dwest*∗*EI* has statistically significant negative elasticities at a level of 1%, which means that for the western area, the *EI* elasticity is much lower than that in eastern and central regions. *Dwest*∗*IS* has negative coefficients, and in result (6-3), the confidence level is 5%, whereas in results (6-4), (6-5) and (6-6), the level is 1%. These results indicate that for the western area, when the share of tertiary industry increases by 1%, the total CO_2 emissions would decrease by at least 2.311%, other factors remaining constant. *Dwest**ln(*IVD*) has positive elasticities which are statistically significant at a confidence level of 1%, indicating that the ln(*IVD*) of western area has larger elasticities than that of the eastern and central areas, although the ln(*IVD*) also has a positive effect on total CO_2 emissions for these two areas. The coefficient of ln(*IVD*) in the eastern and western areas (when *Dwest* = 0) in result (6-6) is 0.848, whereas this coefficient is 1.347 for the ln(*IVD*) in the western area, indicating that a 1% increase in industrial value-added production will lead to a 1.347% increase in the total CO_2 emissions, which is 0.499% higher than in the eastern and central areas. The coefficient of *Dwest**ln(*PEM*) is negative and

Table 6
OLS regression at the regional level: western region.

Variables	(6-1) ln(CO_2)	(6-2) ln(CO_2)	(6-3) ln(CO_2)	(6-4) ln(CO_2)	(6-5) ln(CO_2)	(6-6) ln(CO_2)
ln(*PEM*)	0.240***	0.203**	0.193**	0.193**	0.176**	0.164*
	(0.078)	(0.095)	(0.091)	(0.089)	(0.087)	(0.089)
ln(*IVD*)	0.844***	0.823***	0.891***	0.882***	0.868***	0.848***
	(0.083)	(0.082)	(0.089)	(0.093)	(0.097)	(0.116)
ln(*RD*)	−0.038	−0.097	−0.017	−0.181	−0.235*	−0.289
	(0.078)	(0.096)	(0.091)	(0.125)	(0.140)	(0.203)
ES	−0.431	−0.732	−0.271	−1.121	−2.163	−2.471
	(3.364)	(3.418)	(3.385)	(3.393)	(3.570)	(3.747)
EI	2.196***	2.102***	2.412***	2.314***	2.274***	2.208***
	(0.193)	(0.244)	(0.273)	(0.270)	(0.274)	(0.314)
IS	−2.408***	−2.026**	−1.339	−0.806	−0.624	−0.474
	(0.605)	(0.936)	(0.950)	(1.007)	(1.037)	(1.113)
*Dwest*EI*	−1.258***	−1.152***	−1.639***	−1.665***	−1.607***	−1.553***
	(0.189)	(0.254)	(0.291)	(0.280)	(0.281)	(0.311)
*Dwest*IS*		−0.751	−2.311**	−3.843***	−4.665***	−4.550***
		(0.921)	(1.078)	(1.213)	(1.386)	(1.355)
*Dwest**ln(*IVD*)			0.193***	0.450***	0.412***	0.499***
			(0.058)	(0.094)	(0.086)	(0.157)
*Dwest**ln(*PEM*)				−0.782***	−0.744***	−0.623***
				(0.238)	(0.227)	(0.169)
*Dwest*ES*					13.80**	12.50**
					(6.439)	(5.852)
*Dwest**ln(*RD*)						0.162
						(0.195)
Constant	0.131	0.0761	−0.407	−0.995**	−1.062**	−1.111**
	(0.419)	(0.427)	(0.434)	(0.487)	(0.496)	(0.508)
Observations	100	100	100	100	100	100
R-squared	0.787	0.788	0.802	0.809	0.812	0.813

Standard errors in parentheses.
*** $p < .01$.
** $p < .05$.
* $p < .1$.

statistically significant, indicating that larger industrial parks may have lower CO_2 emissions in the western area. The positive sign of the elasticities of *Dwest*ES* indicate that the increased proportion of clean energy may lead to an increase in the total carbon emissions of industrial parks in the western region.

6. Conclusion and policy implication

Using panel data covering 20 industrial parks in China for the period 2012–2016, this paper analyzed the linear effects of industry value-added output, employment population, R&D intensity, energy structure, energy intensity and industrial structure on CO_2 emissions with STIRPAT model. The overall analysis results confirm that the increase in output and energy intensity is a dominant contributor to the growth of CO_2 emissions whereas the increase of the share of tertiary industry and R&D intensity have significant effects on reducing CO_2 emissions. These findings indicate a set of policies for industrial parks to realize low-carbon and sustainable growth: (i) accelerating the elimination of obsolete and excess production capacity in GHG-intensive sectors; (ii) improving the development of low-carbon technology in heavy industries; (iii) optimizing the industrial structure by promoting the development of tertiary industry, especially the high value-added and low carbon intensive industries.

With distinct economic development levels and industrial structures, Chinese regions exhibit evident spatial differences and industrial heterogeneity. We conduct further analysis considering regional difference by adding dummy variables in the model.

The regional analysis results shed light on the different development mode of industrial parks in different areas of China. For the eastern region, the increase in the share of renewable energy will significantly decrease CO_2 emissions. This may be attributed to the fact that exploiting renewable energy is an effective way to reduce carbon emissions for industrial parks in this area. In the central and western areas an increase in renewable energy consumption is projected to cause an increase in CO_2 emissions, which is counter-intuitive. Possible explanations include the fact that the proportion of renewable energy as a percentage of total energy consumption is too low to affect CO_2 emissions. Another possibility is that in the central and western regions renewable energy is not efficiently used in production process. The western area lacks efficient energy management, proper distribution of renewable energy and smart grid development. The central area may also have lower efficiency in terms of renewable energy utilization.

The future pathways for low carbon development in eastern industrial parks should consider our study's findings that a 1% increase in energy intensity in the eastern region will result in more CO_2 emissions than would be the case in the central and western regions. Therefore our study makes the case that the eastern region is not suitable for the development of additional high energy intensity industries. Implementing low carbonisation cross-cutting and cost-effective technologies to improve the energy efficiency will be crucial.

The regional results also support the idea that labour intensive industries could play an important role in the low-carbon economic development in the central and western region of China. There are numerous hi-tech industry development zones locate in the central region.

Compared to the traditional heavy industrial parks, most hi-tech industrial parks have lower carbon emissions and lower energy consumption per unit of value added and can offer numerous job opportunities. An effective way to realize the low-carbon development for the industrial parks in the central region is to take advantage of the rich human resources in central and western China.

As agglomeration zones for production, industrial parks will remain a major contributor to China's energy consumption and GHG emissions. The low-carbonization process of China's industrial sectors is of great importance for reaching the country's commitments of combating climate change and maintaining long-term sustainable development. The LCIPPP has an important role to play in this process. It provides valuable insights for industrial low-carbon transformation and the implementation of the concept of low-carbon development in spatial planning, industrial development and infrastructure design for industrial parks. Industrial parks across China are made up of a diverse range of activities and product manufacturing. Hence, it is important to enact specific policies according to the regions and industries for the low-carbonization of industrial parks. There is no single and unifying approach for all of the industrial parks. The strategies to approach low-carbon development must differ, thus making them more deserving of policy attention.

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